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A NEURAL NETWORK WITH MODULAR HIERARCHICAL LEARNING AWARDS ABSTRACT

This invention provides a new hierarchical approach for supervised neural learning of time dependent trajectories. The modular hierarchical methodology leads to architectures which are more structured than fully interconnected networks. The networks utilize a general feedforward flow of information and sparse recurrent connections to achieve dynamic effects. The advantages include the sparsity of units and connections, the modular organization. A further advantage is that the learning is much more circumscribed learning than in fully interconnected systems. The present invention is embodied by a neural network including a plurality of neural modules each having a pre-established performance capability wherein each neural module has an output outputting present results of the performance capability and an input for changing the present results of the performance capability. For pattern recognition applications, the performance capability may be an oscillation capability producing a repeating wave pattern as the present results. In the preferred embodiment, each of the plurality of neural modules includes a pre-established capability portion and a performance adjustment portion connected to control the pre-established capability portion.

JPL Case No. P-19077

Patent Application

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A NEURAL NETWORK WITH MODULAR HIERARCHICAL LEARNING

BACKGROUND OF THE INVENTION

Origin of the Invention:

The invention described herein was made in the performance of work under a NASA contract, and is subject to the provisions of Public Law 96-517 (35 USC 202) in which the contractor has elected not to retain title.

Technical Field:

This invention relates to neural networks and, more particularly, to methods and apparatus wherein a modular hierarchical approach is employed to increase the learning potential and shorten the learning time for such networks.

Background Art:

Artificial neural networks aim to provide complex information processing, comparable to that of biological systems. To reach this goal, versatile methods of "learning" must be available. That is, the neural networks must learn from some sort of a learning and/or teaching process. Learning, of course, is a fundamental ability of biological systems. In the prior art, the most successful approaches to learning have been either the back-propagation or gradient descent method. Although very powerful on relatively simple prob-

lems, theoretical analysis and simulations show that these approaches break down as soon as sufficiently complex problems are considered. A solution applicable to complex problems has been eagerly anticipated in the neural network arts.

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The reason for this is depicted in greatly simplified form in FIG. 1. The typical prior art neural network computing system 10 includes a fully interconnected neural network 12. There are a plurality of outputs 14 connected to a learning function 16. The synaptic weights and neural gains within the network 12 can be changed and adjusted by the learning function 16 over the lines 18 and 20, respectively. Learning takes place according to the techniques of the particular approach applied by adjusting the various synaptic weights and neural gains within the neural network 12 until the desired output response is achieved as a result of known inputs 22. Again, this is a very simplistic representation of a complex structure and methodology presented only for the proposition that the neural network 12 in the prior art is a fully interconnected network that basically starts from scratch with a clean slate in the learning process.

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Learning is a fundamental ability of biological systems. Understanding its principles is also key to the design of intelligent circuits, computers and machines of various kinds. To this date, the most successful approach to learning from an engineering standpoint has been the back-propagation approach or gradient descent approach. In this framework, in the course of learning from examples, the parameters of a learning system, such as a neural network, are adjusted incrementally so as to optimize by gradient descent a suitable function measuring the performance of the system at

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any given time. Although very powerful on relatively simple problems, theoretical analysis and simulations show that this approach breaks down as soon as sufficiently complex problems are considered. Gradient descent learning applied to an
 5 amorphous learning system is bound to fail. (The present invention described below overcomes this fundamental limitation.)

10 An example from the prior art is now described for the basic problem of trajectory learning in neural networks. The ideas involved, however, extend immediately to more general computational problems.

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Consider the problem of synthesizing a neural network capable of producing a certain given non-trivial trajectory. To fix the ideas, we can imagine that the model neurons in
 20 the network satisfy the usual additive model equations

$$\frac{du_i}{dt} = -\frac{u_i}{\tau_i} + \sum_j w_{ij} f(u_j) + I_i \quad (1)$$

25 The learning task is to find the right parameter values, for instance for the synaptic weights w_{ij} , the charging time constants τ_i and the amplifiers gains, so that the output units of the network follow a certain prescribed trajectory $u^*(t)$ over a given time interval $[t_0, t_1]$. For instance, a typical
 30 benchmark trajectory in the literature is a circle or a figure eight, as in FIG. 2. Networks corresponding to Equation (1) above have been successfully trained, although through lengthy computer runs, on figure eights using a form of gradient descent learning for recurrent networks. Consider now
 35 the problem of learning a more complicated trajectory, such as a double figure eight (i.e., a set of four loops joined at

one point), as in FIG. 3. Although the task appears only slightly more complicated, simulations show that a fully interconnected set of units will not be able to learn this task by indiscriminate gradient descent learning on all of its parameters. Thus a different approach is needed.

Biology seems to have overcome the obstacles inherent to gradient descent learning through evolution. Learning in biological organisms is never started from a tabula rasa. Rather, a high degree of structure is already present in the neural circuitry of newly born organisms. This structure is genetically encoded and the result of evolutionary tinkering over time scales several times larger than those of continental drift.

Little is known of the interaction between the prewired structure and the actual learning. One reasonable hypothesis is that complex tasks are broken up into simpler modules and that learning, perhaps in different forms, can operate both within and across modules. The modules in turn can be organized in a hierarchical way, all the way up to the level of nuclei or brain areas. The difficult problem then becomes how to find a suitable module decomposition and whether there are any principles for doing so (in particular, the solutions found by biology are probably not unique). One trick used by evolution seems to have been the duplication, by error, of a module together with the subsequent evolution of one of the copies into a new module somehow complementary of the first one. But this is far from yielding any useful principle and may, at best, be used in genetic type of algorithms, where evolutionary tinkering is mimicked in the computer.

As stated earlier, learning is a fundamental ability of biological systems. It would seem, therefore, that understanding and applying its principles might also be a key to the design of intelligent circuits and computers. In other words, to overcome the fundamental limitation of the prior art as discussed above, there might well be a solution which could be inspired by and based on biological networks. Since a high degree of structure is already present in the neural circuitry of newly born organisms, perhaps one should employ a hierarchical and modular approach whereby a certain degree of structure is initially introduced in the learning system at "birth".

Wherefore, it is an object of this invention to provide an artificial neural network based on the principles of biological neural networks.

It is another object of this invention to provide a neural network employing a hierarchical and modular approach whereby a certain degree of structure is initially introduced in the learning system.

Other objects and benefits of this invention will become apparent from the description which follows hereinafter when read in conjunction with the drawing figures which accompany it.

SUMMARY OF THE DISCLOSURE

The present invention includes a hierarchical and modular

approach, directly inspired from biological networks, whereby a certain degree of structure is introduced in the learning system. The basic organization of the system consists of a hierarchy of modules. The lowest levels of the hierarchy serve as
5 primitives or basic building blocks for the successive levels.

The present invention is embodied in a neural network
10 including a plurality of neural modules each having a pre-established performance capability wherein each neural module has an output outputting a present results of the performance capability and an input for changing the present results of the performance capability. For pattern recognition
15 applications, the performance capability may be an oscillation capability producing a repeating wave pattern as the present results.

20 In the preferred embodiment, each of the plurality of neural modules includess a pre-established capability portion having an output therefrom, and a performance adjustment portion connected to control the pre-established capability
25 portion.

Further in the preferred embodiment, a first group of the plurality of neural modules is on a first hierarchical level; and, a second group of the plurality of neural modules is
30 on a second hierarchical level. Additionally, the first group of the plurality of neural modules controls the second group of the plurality of neural modules. For pattern recognitions applications and the like, the first group of the plurality of
35 neural modules produces a first portion of a desired time dependent pattern: and, the second group of the plurality of

neural modules receives the first portion and forms a second portion of the desired time dependent pattern therefrom.

5 In a three level hierarchy embodiment, a first group of the plurality of neural modules is on a first hierarchical level; a second group of the plurality of neural modules is on a second hierarchical level; a third group of the plurality of neural
10 modules is on a third hierarchical level; the first group of the plurality of neural modules controls the second group of the plurality of neural modules; the second group of the plurality of neural modules controls the third group of the plurality of neural modules; the first group of the plurality of neural
15 modules produces a first portion of a desired time dependent pattern; the second group of the plurality of neural modules receives the first portion and forms a second portion of the desired time dependent pattern therefrom; and, the third
20 group of the plurality of neural modules receives the second portion and forms the desired time dependent pattern therefrom.

25 BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a greatly simplified drawing of a prior art neural network system.

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FIG. 2 is a drawing of a single figure eight pattern.

35 FIG. 3 is a drawing of a double figure eight pattern.

FIG. 4 is a block diagram of a neural module as employed in the present invention.

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FIG. 5 is a greatly simplified drawing in the manner of FIG. 1 showing how in the present invention the neural network is composed of neural modules as in FIG. 4.

10

FIG. 6 is a functional block diagram of a hierarchical structure of neural modules as may be employed in the present invention.

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FIG. 7 is a functional block diagram as in FIG. 6 wherein the neural modules include adjustable oscillators and control modules as may be employed with the present invention when generating time dependent patterns.

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FIG. 8 is the structure of FIG. 7 with the outputs of each of the modules shown when in the process of generating the double figure eight pattern of FIG. 3.

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FIG. 9 depicts a target oval against the actual oval produced by Layer 1 modules of FIG. 8 in laboratory tests thereof.

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FIG. 10 depicts a target single figure eight against the actual figure eight produced by Layer 2 modules of FIG. 8 in laboratory tests thereof.

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DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

5 One common use of neural network systems is the generation of desired patterns which can then be used for such applications as pattern recognition, and the like. Since the present invention as tested to date has been for such applications, its structure for pattern generation will be employed
10 as the example hereinafter and in the accompanying drawings. It is to be understood, however, that the invention is not limited to this single use and variations within the scope and spirit of this disclosure are to be considered as part of
15 the invention being disclosed and to be covered hereby and the claims appended hereto.

20 The basic organization of the solution described herein consists of a hierarchy of modules, where each module can be viewed essentially as an oscillator. The modules, in turn, are organized in a hierarchical way. All the modules within one level of the hierarchy control the output of the modules
25 located in the previous layer. This solution leads to architectures which are more structured than fully interconnected networks, with a general feedforward flow of information and sparse recurrent connections to achieve dynamic effects. The sparsity of the connections as well as the modular organization makes the hardware implementation of the methodology
30 very easy and attractive. The approach presented here has been applied to a simple example of trajectory learning of a semi figure eight. The principles involved extend immediately to more general computational problems.
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A single module 24 of a neural network according to the present invention is depicted in FIG. 4. Unlike the fully interconnected structure of prior art neural networks which has no inherent capability, the module 24 comprises a pre-established capability 26 and a performance adjustment 28 of that capability. There is an output line 30 outputting the instantaneous results of the capability 26 and in input line 32 which allows the performance adjustment 28 to be modified by a previous layer module. As we will see shortly, in our specific example the capability 26 is an oscillator while the adjustment 28 is an ability to adjust the parameters of the oscillator.

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A system 10' according to the present invention is depicted in FIG. 5 wherein the neural network 12' comprises a plurality of neural modules 24 which can be connected in a hierarchical structures as necessary. A three level structure of modules 24 is depicted in FIG. 6. The same three level structure designating the modules 24 as adjustable oscillators is shown in FIG. 7. The outputs of the modules 24 when forming a double figure eight as the ultimate output according to the example now to be described in detail is shown in FIG. 8.

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The inventors herein have taken inspiration from the biological analogy discussed previously herein to tackle the problem of creating specific complex trajectories in a neural network. Although it is difficult at this stage to keep a close analogy with biology, it may be useful to think of the problem of central pattern generation or motor control in natural organisms. In order to construct a neural network capable of producing a double figure eight, we introduce a certain

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degree of organization in the system prior to any learning. The basic organization of the system consists of a hierarchy of modules. In this particular example, each module 24 can be viewed essentially as an oscillator. The modules, in turn,
5 are organized in a hierarchical way as described above. For the time being, all the modules 24 within one level of the hierarchy control the output of the modules 24 located in the previous layer.

10

At the bottom of the hierarchy, in the first level, there is a family of simple and possibly independent modules, each one corresponding to a circuit with a small number of units
15 capable of producing some elementary trajectory, such as a sinusoidal oscillation. In the case of the additive model, these could be simple oscillator rings with two or three neurons, an odd number of inhibitory connections and sufficiently high gains. Thus, in one example, the first level of the hierarchy
20 could contain four oscillator rings, one for each loop of the target trajectory, as depicted in FIG. 8. The parameters in each one of these four modules 24 can be adjusted, by gradient descent or random descent or some other optimization
25 procedure, in order to match each one of the loops in the target trajectory.

The second level of the pyramid preferably contains two
30 control modules. Each one of these modules 24 controls a distinct pair of oscillator networks from the first level, so that each control network in the second level ends up producing a simple figure eight (as shown in FIG. 8). Again, the control networks in level two can be oscillator rings and their
35 parameters can be adjusted. In particular, after the learning process is completed, they should be operating in their

high-gain regimes and have a period equal to the sum of the periods of the circuits each one controls.

5 Finally, the third layer consists of another oscillatory and adjustable module 24 which controls the two modules 24 in the second level so as to produce a double figure eight. The third layer module 24 must also end up operating in its high-
10 gain regime with a period equal to four times the period of the oscillators in the first layer. In general, the final output trajectory is also a limit cycle because it is obtained by superimposition of limit cycles in the various modules. If the
15 one another, it is preferable to provide for adjustable delays between the various modules 24 in order to get the proper harmony among the various phases. In this way, a sparse network with 20 units or so can be constructed which can
20 successfully execute a double figure eight. The importance of the effects of delays and adjustable delays in these architectures and their ubiquitous presence in natural neural systems has also lead us to conduct an analytical study of the effect of
25 delays on neural dynamics (especially oscillatory properties) and learning. The main result of our study is that delays tend to increase the period of oscillations and broaden the spectrum of possible frequencies in a quantifiable way. A recurrent back-propagation learning algorithm can be derived
30 for adjustable delays.

35 There are actually different possible neural network realizations depending on how the action of the control modules 24 is implemented. For instance, if the control units are gating the connections between corresponding layers, this amounts to using higher order units in the network. The

number of layers in the network then becomes a function of the order of the units one is willing to use. Alternatively, one could assume the existence of a fast weight dynamics on certain connections governed by a corresponding set of differential equations.

It is clear that this approach which combines a modular hierarchical architecture together with some simple form of learning can be extended to general trajectories. At the very least, one could always use Fourier analysis to decompose a target trajectory into a superimposition of sinusoidal oscillations of different frequencies and use, in the first level of the hierarchy, a corresponding large bank of oscillators networks (although this decomposition may not be the most economical). One could also use damped oscillators to perform some sort of wavelet decomposition. Although we believe that oscillators with limit cycles present several attractive properties (such as stability, short transients, biological relevance, for example), one can conceivably use completely different circuits as building blocks in each module. Another observation is that the problem of synthesizing a network capable of certain given trajectories is more general than what would seem at first sight. In fact, any computation can be viewed as some sort of trajectory in the state space of a computing device, whether digital or analog.

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The modular hierarchical approach of the present invention leads to architectures which are more structured than fully interconnected networks, with a general feedforward flow of information and sparse recurrent connections to achieve dynamical effects. The sparsity of units and connections are attractive features for hardware design: and so is also the

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modular organization and the fact that learning is much more circumscribed than in fully interconnected systems. In these architectures, some form of learning remains essential, for instance to fine tune each one of the modules. This, in it-
 5 self, is a much easier task than the one a fully interconnected and random network would have been faced with. It can be solved by gradient or random descent or other methods.

10

Example of Numerical Simulations:

The new learning paradigm, presented in the preceding section, has been applied to the problem of learning a figure eight trajectory. Results referring to this problem obtained
 15 using prior techniques can be found in the literature.

We assume that the desired trajectory of a semi-figure eight is composed of two circles and given by:

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$$D_1 = C_1 [x_{10} + \cos(t)] + (1 - C_1)[y_{10} - \cos(t)] \quad (2a)$$

$$D_2 = C_1 [x_{20} + \sin(t)] + (1 - C_1)[y_{20} + \sin(t)] \quad (2b)$$

25

in which C_1 is a square wave with a period of 4π , given by the following equation;

$$C_1 = \text{sign}[\sin(t/2)] \quad (3)$$

30

and $x_{10}, x_{20}, y_{10}, y_{20}$ are the coordinates of the center of the left and right circles respectively. Plotting D_1 vs. D_2 will produce the desired semi-figure eight.

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The basic module of the hierarchical approach for this trajectory is a simple oscillatory ring network with four neurons. The activation dynamics of each unit in the module is

given by:

$$\frac{du_i}{dt} = -\frac{u_i}{\tau_i} + w_{i-1}V_{i-1} \quad i = 1, \dots, 4 \quad (4)$$

5 where $V_0 = V_4$ and V_i is the output of neuron i given by;

$$V_i = \tanh(\gamma_i u_i) \quad (5)$$

10 An odd number of inhibitory connections is required for stable oscillations. At this stage for simplicity, we assume that $w_i = w$ for $i = 1, 3, 4$, $w_2 = -w$ and $\tau_i = \tau$, $\gamma_i = \gamma$ for $i = 1, \dots, 4$. The module is trained to produce a circle through a sinusoidal wave with period of 2π . The initial value of the network parameters, i.e., w, τ and γ are set to
 15 one at the beginning of the learning procedure. To update the network parameters, a gradient descent algorithm based upon the forward propagation of the error is used. After the training, the network parameters converge to the following
 20 values, $w = 1.025$, $\tau = 0.972$ and $\gamma = 1.526$. With these values, after a brief transition period, the module converges to a limit cycle where each unit has a quasi-sinusoidal activation. The phase shift between two consecutive neurons is about $\pi/4$. Therefore, plotting the activity of neuron 1 and 3
 25 in the module against each other will produce a circle which is close to the desired one as illustrated in FIG. 9.

30 At the second level of the hierarchy is the control module. This module is also chosen to be a simple oscillatory ring network with four neurons. This network is operating in the high gain regime and its period is twice that of the basic modules, i.e., 4π . The network parameters at the beginning
 35 of the learning are set to $w = 0.9$, $\gamma = 10$, and $\tau = 2.58$.

The overall network has two output at any time, Z_1 and Z_2 . Their value is given by:

$$Z_1 = 0.5\{[1+VC(1)] [x_{10}+VN1(1)] + [1-VC(1)] [y_{10}+VN1(3)]\} \quad (6a)$$

$$Z_2 = 0.5\{[1+VC(1)] [x_{20}+VN2(1)] + [1-VC(1)] [y_{20}+VN2(3)]\} \quad (6b)$$

in which $VN1(i)$ and $VN2(i)$ are the output of i^{th} neuron in the first and second modules in the first level of the hierarchy, respectively, where $VC(1)$ is the output of the first neuron in the control module. FIG. 9 shows the semi-figure eight obtained by plotting Z_1 vs. Z_2 .

The convergence time of different modules to their limit cycle may vary. Therefore, it is essential to have a synchronization mechanism that aligns the activity of different units at various modules and levels. One such mechanism that has been adapted in this example is based upon time delays. The value of these delays is adjusted by using gradient descent approach such that the network outputs are in harmony with the desired output.

In summary, the invention provides a new hierarchical approach for supervised neural learning of time dependent trajectories. The modular hierarchical methodology leads to architectures which are more structured than fully interconnected networks, with a general feedforward flow of informa-

tion and sparse recurrent connections to achieve dynamical effects. The sparsity of the connections as well as the modular organization makes the hardware implementation of the methodology very easy and attractive. This approach has been applied to an example of trajectory learning of a semi-figure eight.

While the invention has been described in detail by specific reference to preferred embodiments, it is understood that variations and modifications thereof may be made without departing from the true scope of the invention.

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A NEURAL NETWORK WITH MODULAR HIERARCHICAL LEARNING

ABSTRACT OF THE INVENTION

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This invention provides a new hierarchical approach for supervised neural learning of time dependent trajectories. The modular hierarchical methodology leads to architectures which
10 are more structured than fully interconnected networks. The networks utilize a general feedforward flow of information and sparse recurrent connections to achieve dynamic effects. The advantages include the sparsity of units and connections,
15 the modular organization. A further advantage is that the learning is much more circumscribed learning than in fully interconnected systems. The present invention is embodied by a neural network including a plurality of neural modules
20 each having a pre-established performance capability wherein each neural module has an output outputting present results of the performance capability and an input for changing the present results of the performance capability. For pattern
25 recognition applications, the performance capability may be an oscillation capability producing a repeating wave pattern as the present results. In the preferred embodiment, each of the plurality of neural modules includes a pre-established capability portion and a performance adjustment portion connected to control the pre-established capability portion.
30

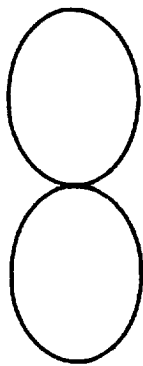
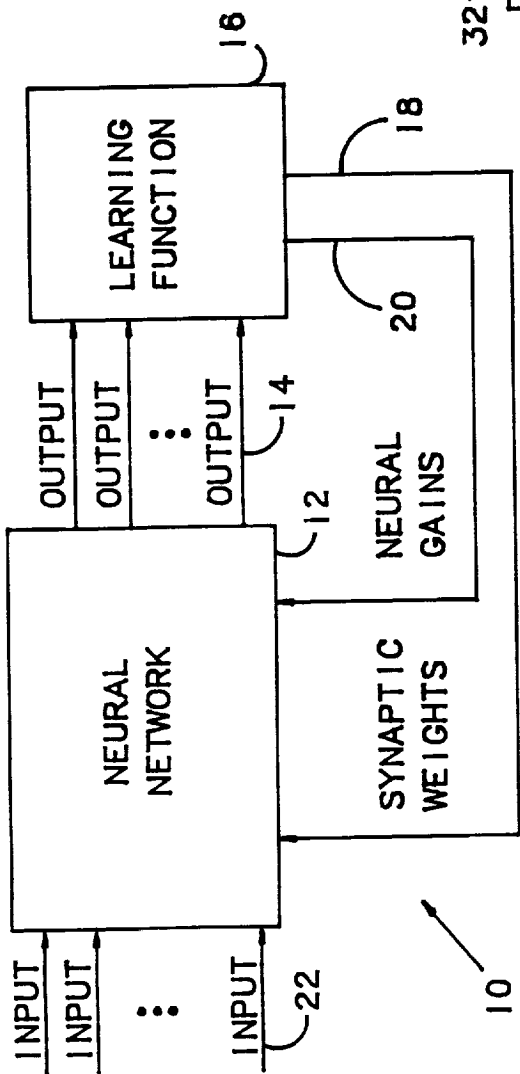


FIG. 2

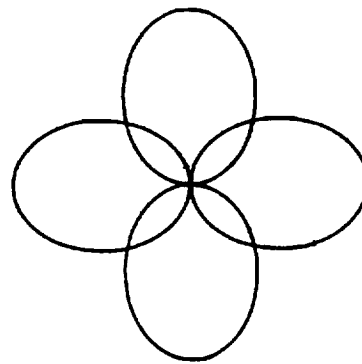
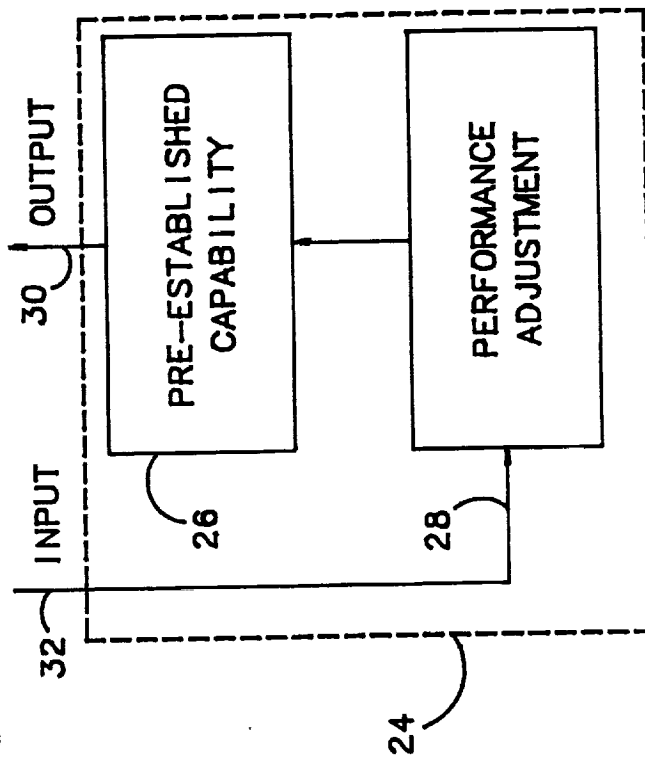


FIG. 3



FIG. 5

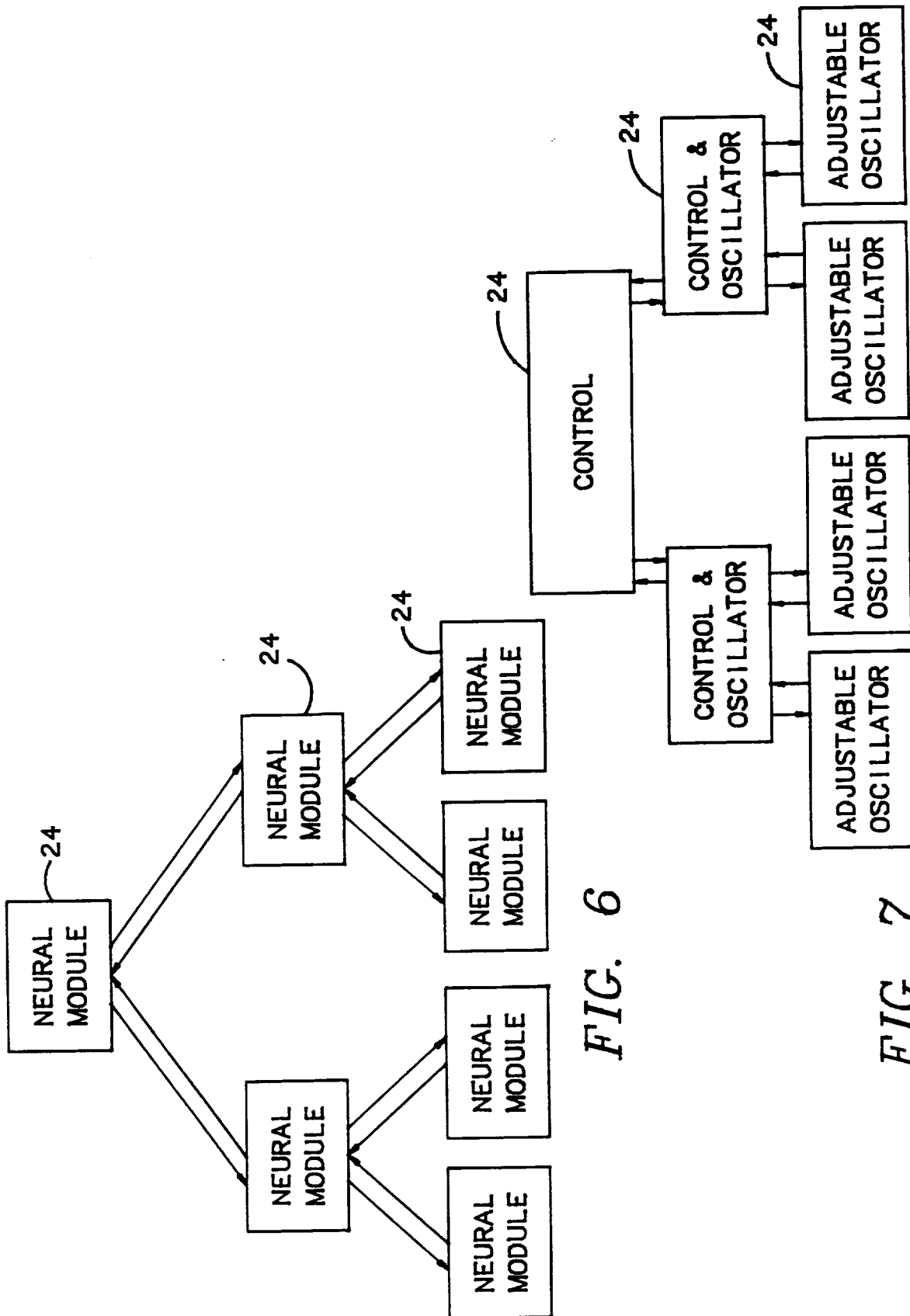


FIG. 6

FIG. 7

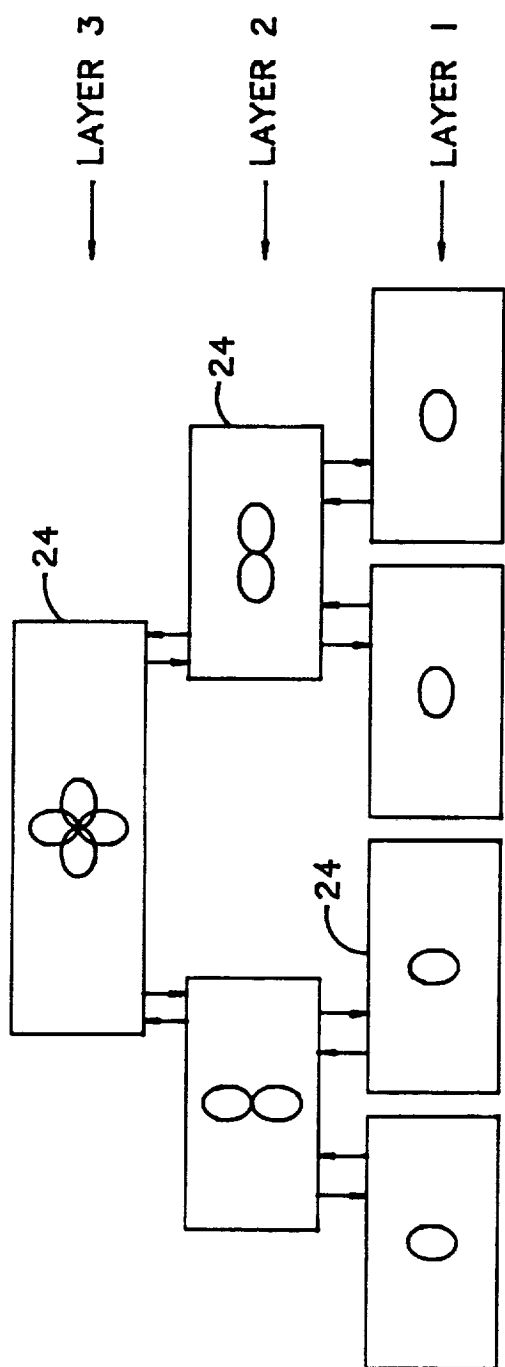


FIG. 8

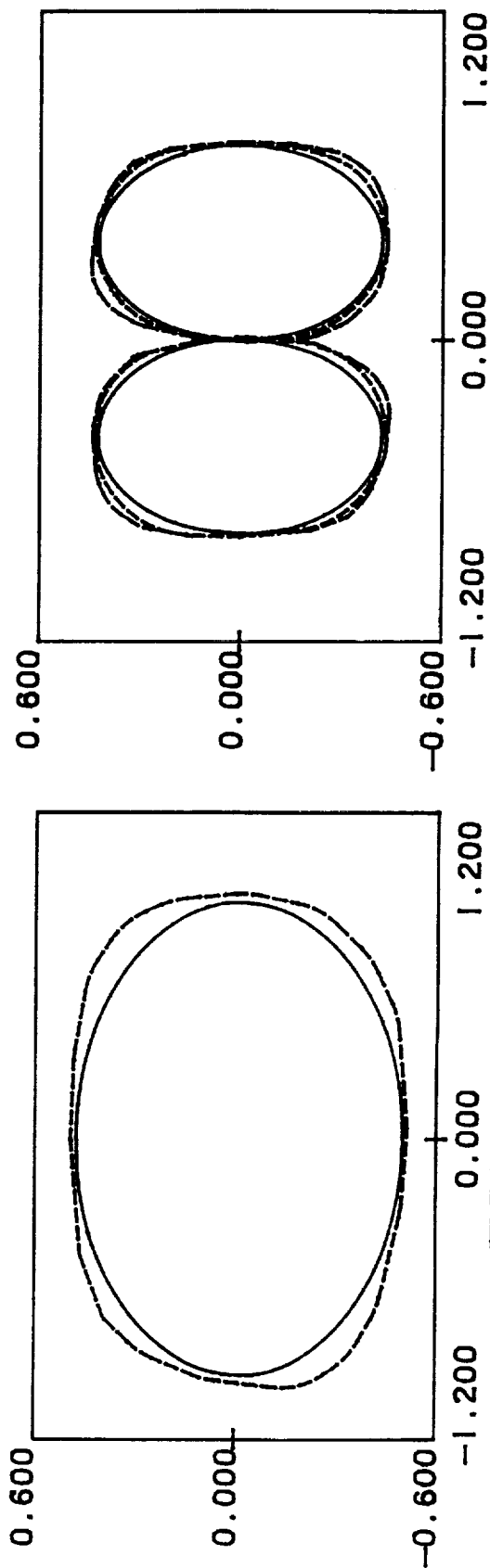


FIG. 10

FIG. 9